

Wheat Biomass Estimation in Different Growth Stages Based on Color and Texture Features of UAV Images

DAI Mian^{1,2}, YANG Tianle^{1,2}, YAO Zhaosheng^{1,2}, LIU Tao^{1,2}, SUN Chengming^{1,2*}

(1. Jiangsu Key Laboratory of Crop Genetics and Physiology/Jiangsu Key Laboratory of Crop Cultivation and Physiology, Agricultural College, Yangzhou University, Yangzhou 225009, China; 2. Jiangsu Co-Innovation Center for Modern Production Technology of Grain Crops, Yangzhou University, Yangzhou 225009, China)

Abstract: In order to realize the rapid and non-destructive monitoring of wheat biomass, field wheat trials were conducted based on different densities, nitrogen fertilizers and varieties, and unmanned aerial vehicle (UAV) was used to obtain RGB images in the pre-wintering stage, jointing stage, booting stage and flowering stage of wheat. The color and texture feature indices of wheat were obtained using image processing, and wheat biomass was obtained by manual field sampling in the same period. Then the relationship between different color and texture feature indices and wheat biomass was analyzed to select the suitable feature index for wheat biomass estimation. The results showed that there was a high correlation between image color index and wheat biomass in different stages, the values of r were between 0.463 and 0.911 ($P < 0.05$). However, the correlation between image texture feature index and wheat biomass was poor, only 5 index values reached significant or extremely significant correlation level. Based on the above results, the color indices with the highest correlation to wheat biomass or the combining indices of color and texture features in different growth stages were used to construct estimation model of wheat biomass. The models were validated using independently measured biomass data, and the correlation between simulated and measured values reached the extremely significant level ($P < 0.01$), and root mean square error (RMSE) was smaller. The R^2 of color index model in the four stages were 0.538, 0.631, 0.708 and 0.464, and RMSE were 27.88, 516.99, 868.26 and 1539.81 kg/ha, respectively. The R^2 of the model combined with color and texture index were 0.571, 0.658, 0.753 and 0.515, and RMSE were 25.49, 443.20, 816.25 and 1396.97 kg/ha, respectively. This indicated that the estimated results using the models were reliable and accurate. It also showed that the estimation models of wheat biomass combined with color and texture feature indices of UAV images were better than the single color index models.

Key words: wheat; UAV image; color index; texture feature index; biomass; texture index

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Biography: DAI Mian (1998—), female, postgraduate, research interest: intelligent monitoring of crop growth. E-mail: 996982850@qq.com.

*Corresponding author: SUN Chengming (1973—), male, Ph.D., professor, research interest: smart agriculture. E-mail: cmsun@yzu.edu.cn.

1 Introduction

Biomass is an important physical and chemical parameter in ecosystems and a significant index for assessing the life activities of vegetation and for monitoring growth and estimating crop yield^[1]. Traditional biomass estimation methods are not only time-consuming and labor-intensive, but also can not conduct large-scale monitoring^[2]. The rapid development of remote sensing technology in recent years has accelerated its wide application in crop biomass estimation, as it is fast, accurate, and non-destructive^[1].

Based on the spectral features of vegetation, previous studies have obtained many achievements in using vegetation indices to estimate biomass. Jimenez-Sierra et al.^[3] proposed GBF-Sm-Bs approach by obtaining biomass estimation correlation of 0.995 with $R^2 = 0.991$. This result increased the precision in the biomass estimation by about 62.43% compared to previous work. Hou et al.^[4] built a biomass estimation model based on multiple vegetation indices, of which the index model of red edge location was used to estimate the wheat biomass model, R^2 were all greater than 0.8. Liu et al.^[5] used arbor as an object to analyze the correlation between biomass and biomass factors, and constructed a highly accurate forest biomass estimation model using the partial least-squares method, the correlation coefficient between the predicted value and the measured value was 0.718, and the accuracy was 90.1%. However, the vegetation index is not sensitive to canopy biomass changes in high-density scenarios and deviates easily when inverting physical and chemical parameters or even agronomic parameters, thus affecting the accuracy of the estimation model^[6]. In response, some scientists have added texture feature information to the spectral features to improve saturation when only spectral informa-

tion is available, as well as to improve the spatial and temporal discrimination of image information and the estimation potential of agronomic parameters^[7].

Some researchers have quantitatively analyzed the application of texture features in agronomic parameters. Gu et al.^[8] studied vegetation coverage and found that the combination of vegetation indices and texture feature indices could improve the accuracy of vegetation coverage estimation. Sarker and Nichol^[9] assessed the biomass of arbor forest and found that the combination of vegetation indices and texture features was better at biomass estimation. Cao et al.^[10] extracted the texture features and spectral features of thematic mapper images and established a biomass regression estimation model, which could effectively estimate the biomass of mangrove wetlands. Mu et al.^[11] constructed a multivariate regression model of vegetation indices, texture features, and vegetation biomass using four typical vegetation indices, and R^2 of the model was 0.713, the minimum RMSE was 98.2543 g/m². Based on the above researches, it was found that the accuracy of the model for estimating biomass in combination with texture features was higher than the accuracy of the model for estimating biomass using a single vegetation index with color features^[12].

In terms of monitoring crop growth based on unmanned aerial vehicle (UAV) images, Lee et al.^[13] used RGB (Red Green Blue) cameras to obtain rice canopy images and found that the absolute value of green light depth (G) simulated by the exponential equation was well correlated with the aboveground biomass and leaf area index (LAI). Wang et al.^[14] demonstrated that the G-R value of rice RGB images had a good relationship with biomass and LAI, which could be used to construct an estimation mod-

el. Wang et al.^[15] used random forest-support vector regression (RF-SVR) model to estimate soil and plant analyzer development (SPAD) values of the wheat canopy and achieved high accuracy ($R^2=0.754$, RMSE=1.716). Yue et al.^[16] combined UAV remote sensing and AquaCrop to estimate winter-wheat biomass, the predicted biomass agreed with the measured values ($R^2=0.61$, RMSE=2.10 t/ha). Shan et al.^[17] used explored the vertical distribution of wheat biomass and found that a linear regression relationship could be better obtained with a single row of wheat images, and the estimation accuracy was also higher than multi-row wheat image.

In this study, UAVs were used to obtain RGB images of wheat in different growth periods, and simultaneous sampling was conducted in the field to determine wheat biomass. The best color and texture feature indices were determined through correlation analysis, and these indices were used to construct the estimation models of wheat biomass in different growth periods based on UAV platform in order to provide a new method for biomass estimation and real-time monitoring of wheat growth in the field.

2 Materials and methods

2.1 Field experiment design

Two experiments were conducted in this study, of which the data from Experiment 1 were used to construct a wheat biomass estimation model and the data from Experiment 2 were used for model validation. Study sites were located in Yizheng city and Zhangjiagang city, Jiangsu province.

2.1.1 Experiment 1 for estimation model

Experiment 1 was conducted in Yizheng from 2018 to 2019. Two wheat varieties of Yangmai23 and Yangfumai4 were selected as the research ob-

jects. Three planting densities were respectively set as: 1 million plants/ha, 1.5 million plants/ha, and 2 million plants/ha. Four nitrogen fertilizer levels were respectively set as: 0 kg/ha, 120 kg/ha, 160 kg/ha, and 200 kg/ha. Nitrogen fertilizers were applied according to the ratio of base fertilizer: new shoots boosting fertilizer: jointing fertilizer: booting fertilizer = 5:1:2:2, and the phosphorus and potassium fertilizers were applied according to the ratio of base fertilizer: jointing fertilizer = 5:5, and the application amounts all were 120 kg/ha. Wheat was planted on November 2, 2016, with a plot area of 16.65 m². Each treatment was repeated twice for a total of 48 experimental plots.

2.1.2 Experiment 2 for model validation

Experiment 2 was conducted in Zhangjiagang from 2017 to 2018. The wheat variety, density, and fertilizer were the same as Experiment 1. Wheat was planted on November 10, 2017, with a plot area of 30 m². Each treatment was repeated twice for a total of 48 experimental plots.

2.2 Data acquisition method

2.2.1 Image acquisition device

The Inspire 1 RAW UAV (DJI, Shenzhen, China) was used for image data acquisition. This UAV is small, powerful, convenient and easy to operate, equipped with a 16-megapixel camera and is able to fly for 15–20 min depending on the load. The remote control was connected to the wireless follower to extend the control distance to 5 km.

2.2.2 Image acquisition

UAV image acquisition runs through the pre-wintering period, jointing period, booting period, and flowering period, and sampling time was about 8:00-10:00 AM or 3:00-5:00 PM. In this study, DJI GS Pro was used to automatically generate flight routes within the designated area, and automatic flight, automatic shooting, and complete relevant

data receiving, processing and sending. The flight route of UAV was s-type, and the flight altitude was set to 15 m. In order to achieve accurate image registration, the image repetition rate was set to 60% on the main route and 70% between the main route during route and point planning. The standard calibration panels were used to perform radiation calibration on RGB band sensors during flight to minimize the influence of constantly changing lighting conditions on RGB images. After the aerial images were collected, the orthophoto image was generated by using the software Pix4DMapper, and the images were stitched together seamlessly through feature matching of adjacent images^[18].

2.2.3 Determination of aboveground biomass

In the pre-wintering period, jointing period, booting period, and flowering period of wheat growth, 15 wheat plants were selected from each plot, the aboveground parts of plants were collected and transported back to the laboratory, and were dried in an oven for 1.5 h at 105 °C and then at 80 °C until constant weight, and then were weighed and converted to biomass per unit area.

2.3 Data analysis and utilization

2.3.1 UAV image preprocessing method

MATLAB2014a software was used for UAV image preprocessing, including image cropping, denoising, smoothing, and sharpening. Image cropping stitches the images into uniform images according to different cells. Denoising eliminates the noise in digital images. Smoothing and sharpening reduce the slope of the image, improve the image quality, and reduce the loss of pixel extraction from the target.

2.3.2 Color indices

Eight commonly used color indices were selected for UAV image data analysis, including visual atmospheric resistance vegetation index (VARI)^[19], excess red vegetation index (ExR)^[20], excess green vegetation index (ExG)^[21], green leaf vegetation index (GLI)^[22], excess green-red difference index (ExGR)^[20], normalized difference index (NDI)^[23], modified green red vegetation index (MGRVI)^[24] and red green blue vegetation index (RGBVI)^[24], as shown in Table 1.

Table 1 Algorithms of color indices

Index	Abbreviation	Computational formula
Visible Atmospheric Resistance Vegetation Index	VARI	$VARI = (g - r) / (g + r)$ (1)
Excess Red Vegetation Index	ExR	$ExR = 1.4r - g$ (2)
Excess Green Vegetation Index	ExG	$ExG = 2g - r - b$ (3)
Green Leaf Vegetation Index	GLI	$GLI = (2g - b - r) / (2g + b + r)$ (4)
Excess Green-Red Difference Index	ExGR	$ExGR = ExG - ExR$ (5)
Normalized Difference Index	NDI	$NDI = (g - r) / (g + r)$ (6)
Modified Green Red Vegetation Index	MGRVI	$MGRVI = (g^2 - r^2) / (g^2 + r^2)$ (7)
Red Green Blue Vegetation Index	RGBVI	$RGBVI = (g^2 - br) / (g^2 + br)$ (8)

2.3.3 Texture feature indices

MATLAB software was used to extract texture features based on a gray level co-occurrence matrix^[25]. Four common texture features were extracted

from the UAV image: angular second moment (ASM), contrast (CON), correlation (COR) and entropy (ENT)^[25], as shown in Table 2.

Table 2 Algorithms of texture feature indices

Index	Abbreviation	Computational formula
Angular Second Moment	ASM	$ASM = \sum_i \sum_j P(i, j)^2$ (9)
Contrast	CON	$CON = \sum_i \sum_j (i - j)^2 P(i, j)$ (10)
Correlation	COR	$COR = \left[\sum_i \sum_j ((i, j) P(i, j)) - \mu_x \mu_y \right] / \sigma_x \sigma_y$ (11)
Entropy	ENT	$ENT = - \sum_i \sum_j P(i, j) \log P(i, j)$ (12)

2.4 Model construction and evaluation

Based on the correlation between image color and texture feature indices and wheat biomass, the color and texture feature indices with the largest correlation coefficient were selected to construct the regression model for biomass estimation (Experiment 1 data). Then the independently measured biomass data were used to validate and evaluate the model based on the coefficient of determination

Table 3 Correlations between different color indices and wheat biomass based on UAV image (n=24)

Growth stage	ExG	VDI	ExR	ExGR	VARI	GLI	MGRVI	RGBVI
Pre-wintering stage	0.594**	0.458*	-0.619**	0.678**	0.743**	0.657**	0.706**	0.598**
Jointing stage	0.813**	0.823**	-0.824**	0.911**	0.817**	0.809**	0.687**	0.625**
Booting stage	0.493*	0.793**	-0.779**	0.607**	0.734**	0.483*	0.817**	0.351
Flowering stage	0.367	0.540**	-0.652**	0.463*	0.679**	0.369	0.540**	0.316

Note: * $P < 0.05$, ** $P < 0.01$ ($r_{0.05}=0.396$, $r_{0.01}=0.505$)

Table 4 Correlations between different texture feature indices and wheat biomass based on UAV image

Growth stage	ASM	CON	COR	ENT
Pre-wintering stage	0.573**	0.195	-0.132	-0.564**
Jointing stage	0.271	0.511**	-0.574**	-0.072
Booting stage	-0.200	0.417*	-0.351	0.260
Flowering stage	-0.222	0.123	-0.167	0.126

(R^2), root mean square error (RMSE), and 1:1 map (Experiment 2 data).

3 Results and analysis

3.1 Correlation between wheat biomass and image color/texture feature indices in different growth periods

Wheat biomass experiences various changes throughout the growth period and undergoes a process of continuous increase. In this study, the data in Experiment 1 were used to quantitatively analyze the correlation between eight color indices as well as four texture feature indices in the main growth periods of wheat and biomass to determine the optimal color index and texture feature index for estimating biomass. The correlation between the different color indices as well as the texture feature indices and wheat biomass based on the UAV image are shown in Table 3 and Table 4.

3.2 Biomass estimation models for wheat growth in different growth periods based on color indices

3.2.1 Model construction

(1) Estimation model of wheat biomass in the pre-wintering period

It can be seen from Table 1 that the correlation between the color indices of the UAV image and biomass was good during this period. Besides NDI, the correlation between the other seven indices and

biomass was extremely significant ($P < 0.01$), among which the correlation of VARI and biomass was the highest, with the correlation coefficient r reaching 0.743. Therefore, the color index VARI was chosen as the independent variable. The wheat biomass estimation model was constructed by using regression analysis:

$$B_1 = 535.9 \times \text{VARI} + 87.9 \quad (13)$$

where B_1 represents the biomass of wheat in the pre-winter period, kg/ha. The coefficient of determination R^2 was 0.553.

(2) Estimation model of wheat biomass in the jointing period

The correlation between the color indices and biomass of the UAV image in the jointing period was the highest, and eight color indices reached a highly significant correlation level. Among them, ExGR had the highest correlation with biomass, and the correlation coefficient r reached 0.911. Therefore, the color index ExGR was selected as the independent variable, and the wheat biomass estimation model is:

$$B_2 = 9054.6 \times \text{ExGR} + 1915.5 \quad (14)$$

where B_2 represents the biomass of wheat in the jointing period, kg/ha. It was constructed using regression analysis, with a coefficient of determination R^2 of 0.804.

(3) Estimation model of wheat biomass in the booting period

With the gradual advancement of wheat growth and the increasing biomass, the color of the UAV image will become saturated, and its correlation with biomass will be correspondingly weakened. The correlation between UAV image color indices and biomass in the booting period was significantly lower than that in the jointing period. Only six indices were significantly correlated. Among them, MGRVI had the highest correlation with bio-

mass, and the correlation coefficient r was 0.817. Therefore, the color index MGRVI was chosen as the independent variable, and the wheat biomass estimation model is:

$$B_3 = 20024.1 \times \text{MGRVI} - 543.2 \quad (15)$$

where B_3 represents the biomass of wheat in the booting period, kg/ha. It was constructed using regression analysis, with an R^2 of 0.670.

(4) Estimation model of wheat biomass in the flowering period

The canopy image in the flowering period contains different types of objects such as the ear and leaf, and the correlation between image color indices and biomass is further reduced. During this period, the correlation between the UAV image color indices and biomass was the lowest among the four periods, three of which being non-significant, one being significantly correlated, and the other four reaching extremely significant levels, of which the correlation of VARI and biomass was the highest and the correlation coefficient r was 0.679. Therefore, the color index VARI was selected as the independent variable, and the wheat biomass estimation model is:

$$B_4 = 42623.1 \times \text{VARI} + 7115.3 \quad (16)$$

where B_4 represents the biomass of wheat in the flowering period, kg/ha. It was constructed using regression analysis, and the R^2 was 0.461.

3.2.2 Model validation

(1) Validation of the wheat biomass estimation model in the pre-wintering period

Independently measured data were used to validate the wheat biomass estimation model in the pre-wintering period and plot the 1:1 relationship between the measured values and the model predictions (Fig. 1(a)). It is evident from the figure that there was high agreement between the predicted and measured values of wheat biomass in the pre-wintering period, and the predicted R^2 of the model

was 0.538. Correlation analysis showed that the correlation between the predicted value and the measured value reached a highly significant level, indicating that the estimation model is feasible. In addition, the simulated RMSE was 27.88 kg/ha, which is relatively small, indicating that the simulation results of the model are relatively reliable.

(2) Validation of the wheat biomass estimation model in the jointing period

The validation results of the estimation model in the jointing period are shown in Figure 1(b). The predicted value of wheat biomass in the jointing period was close to the measured value, and there was high consistency between the two. The predicted R^2 of the model was 0.631, and the effect was better than the pre-wintering period. Correlation analysis indicated that the correlation between the predicted value and the measured value reached a highly significant level, indicating that the estimation model is feasible. In addition, the simulated RMSE was 516.99 kg/ha, which is relatively small, indicating that the simulation results of the model are relatively reliable.

(3) Validation of the wheat biomass estimation model in the booting period

The results of the estimation model in the booting period are shown in Figure 1(c). It can be seen from the figure that the predicted value of wheat biomass in the booting period was close to the measured value, and there was high consistency between the two. The predicted R^2 of the model was 0.708, and the effect was better than the jointing period. Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 868.26 kg/ha, which is relatively small, indicating that the simulation results of the model are rela-

tively reliable.

(4) Validation of the wheat biomass estimation model in the flowering period

The validation results of the estimation model in the flowering period are shown in Figure 1(d). The predicted value of wheat biomass in the flowering period was close to the measured value, and there was a good agreement between the two. The model predicted an R^2 of 0.464, and the effect was the poorest among the four periods. However, the correlation analysis demonstrated a correlation between the predicted value and the measured value, indicating that the estimation model is feasible. In addition, the simulated RMSE was 1539.81 kg/ha, which is relatively small, indicating that the simulation results of the model are relatively reliable.

In summary, the UAV image color indices could be used to estimate wheat biomass in different growth periods, and the effects in the different periods also differed. However, wheat biomass estimation using a single color index did not achieve the best results.

3.3 Wheat biomass estimation models in different growth periods based on color and texture feature indices

3.3.1 Model construction

(1) Estimation model of wheat biomass in the pre-wintering period

It can be seen from Table 4 that the correlation between UAV image texture indices and biomass in the pre-wintering period was high, however, it was poorer than the color indices. Among the four texture feature indices, two were not significantly correlated, whereas the other two were significantly correlated, of which ASM had the highest correlation with biomass, with a correlation coefficient of 0.573. Therefore, the texture feature index

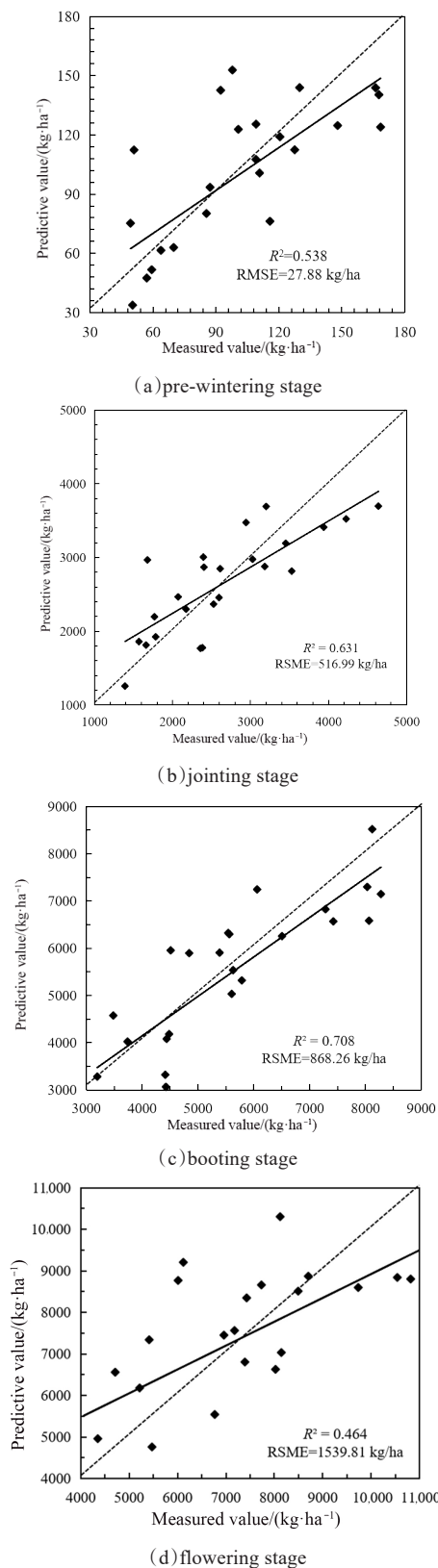


Fig. 1 Verification of wheat biomass estimation models based on color indices

ASM was combined with the color index VARI, and the wheat biomass estimation multiple regression model is:

$$B_5 = 547.9 \times \text{VARI} - 35.9 \times \text{ASM} + 97.2 \quad (17)$$

where B_5 represents the biomass of wheat in the pre-winter period combining VARI and ASM. The R^2 was 0.565, and the accuracy was slightly improved compared with the single color index model (2.17% increase).

(2) Estimation model of wheat biomass in the jointing period

From the pre-wintering period to the jointing period, the UAV image texture indices did not improve significantly. Among the four texture feature indices, only two had a significant correlation with biomass, with COR exhibiting the highest correlation with an r of 0.574 (Table 4). Therefore, the texture feature index COR was combined with the color index ExGR. The wheat biomass estimation multiple regression model is:

$$B_6 = 8762.5 \times \text{ExGR} - 259.4 \times \text{COR} + 2075.8 \quad (18)$$

where B_6 represents the biomass of wheat in the jointing period combining ExGR and COR. The R^2 was 0.833, and the accuracy was improved compared with the single color index model (3.61% increase).

(3) Estimation model of wheat biomass in the booting period

The colors of the wheat UAV images in the booting period showed a certain saturation phenomenon, and the texture feature indices were also affected. Among the four texture feature indices, only CON was significantly correlated with biomass, with an r of 0.417 (Table 4). Therefore, the texture feature index CON was combined with the color index MGRVI, and the wheat biomass estimation multiple regression model is:

$$B_7 = 24027.4 \times \text{MGRVI} - 3098.6 \times \text{CON} + 2252.3 \quad (19)$$

where B_7 represents the biomass of wheat in the booting period combining MGRVI and CON. The R^2 was 0.762, and the accuracy was significantly improved compared with the single color index model (13.73% increase).

(4) Estimation model of wheat biomass in the flowering period

The correlation between UAV image texture feature indices and wheat biomass in the flowering period was relatively low, and the correlation between the four feature indices and wheat biomass did not reach a significant level (Table 4). Therefore, the index ASM with the highest correlation coefficient was selected and combined with the color index VARI. The wheat biomass estimation multiple regression model is:

$$B_8 = 42654.9 \times \text{VARI} - 5595.3 \times \text{ASM} + 8507.9 \quad (20)$$

where B_8 represents the biomass of wheat in the flowering period combining VARI and ASM. The R^2 was 0.485. The accuracy was much higher than the single color index model (5.21% increase).

3.3.2 Model validation

(1) Validation of the wheat biomass estimation model in the pre-wintering period

The independently measured data were used to validate the wheat biomass estimation model in the pre-wintering period, and the 1:1 relationship between the measured values and the model predictions was plotted (Figure 2(a)). There was good agreement between the predicted value of wheat biomass and the measured value in the pre-wintering period. The predicted R^2 of the model was 0.571, which was better than the single color index model (6.13% increase). Correlation analysis showed that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 25.49 kg/ha, which

was smaller than the RMSE of the single color index model (reduced by 8.57%), indicating that the reliability of the model had been further improved.

(2) Validation of the wheat biomass estimation model in the jointing period

The validation results of the jointing estimation model are shown in Fig. 2(b). It can be seen that the predicted value of wheat biomass in the jointing period was close to the measured value, and there was a good agreement between the two. The predicted R^2 of the model was 0.658, which is better than the pre-wintering period, and the prediction accuracy was improved compared to the single color index model (4.28% increase). Correlation analysis indicated that there was a correlation between the predicted value and the measured value, indicating that the estimation model is feasible. The simulated RMSE was 443.20 kg/ha, which was significantly smaller than the RMSE of the single color index model (14.27% decrease), indicating that the reliability of the model had been greatly improved.

(3) Validation of the wheat biomass estimation model in the booting period

The validation results of the booting period estimation model are shown in Fig. 2(c). The predicted value of wheat biomass in the booting period was close to the measured value, and there was high consistency between the two. The model predicted an R^2 of 0.753, which was better than the jointing period, and the prediction accuracy was greatly improved compared to the single color index model (6.36% increase). Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 816.25 kg/ha, which was smaller than the RMSE of the single color index

model (5.99% decrease), indicating that the reliability of the model had been improved.

(4) Validation of the wheat biomass estimation model in the flowering period

The validation results of the flowering period estimation model are shown in Fig. 2(d). The predicted value of wheat biomass in the booting period was close to the measured value, and there was a high agreement between the two. The predicted R^2 of the model was 0.515, and the prediction accuracy was improved compared to the single color index model (10.99% increase). Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 1396.97 kg/ha, which was smaller than the RMSE of the single color index model (reduced by 9.28%), indicating that the reliability of the model had been improved.

Based on the above results, the biomass estimation model of wheat in different growth periods based on the combination of UAV image color and texture feature indices was significantly improved over the single color index model and can be used to estimate the biomass of wheat in different growth periods.

4 Discussion

At present, few studies have monitored growth indices such as wheat biomass using the RGB image data of UAVs. Hunt et al.^[26] obtained wheat canopy images using UAVs and used the vegetation indices NDVI and GNDVI to monitor wheat growth in order to validate the availability of UAV images in wheat growth monitoring. In this study, the RGB images collected in the four key growth periods of wheat were systematically analyzed. The image information was extracted, and eight common color

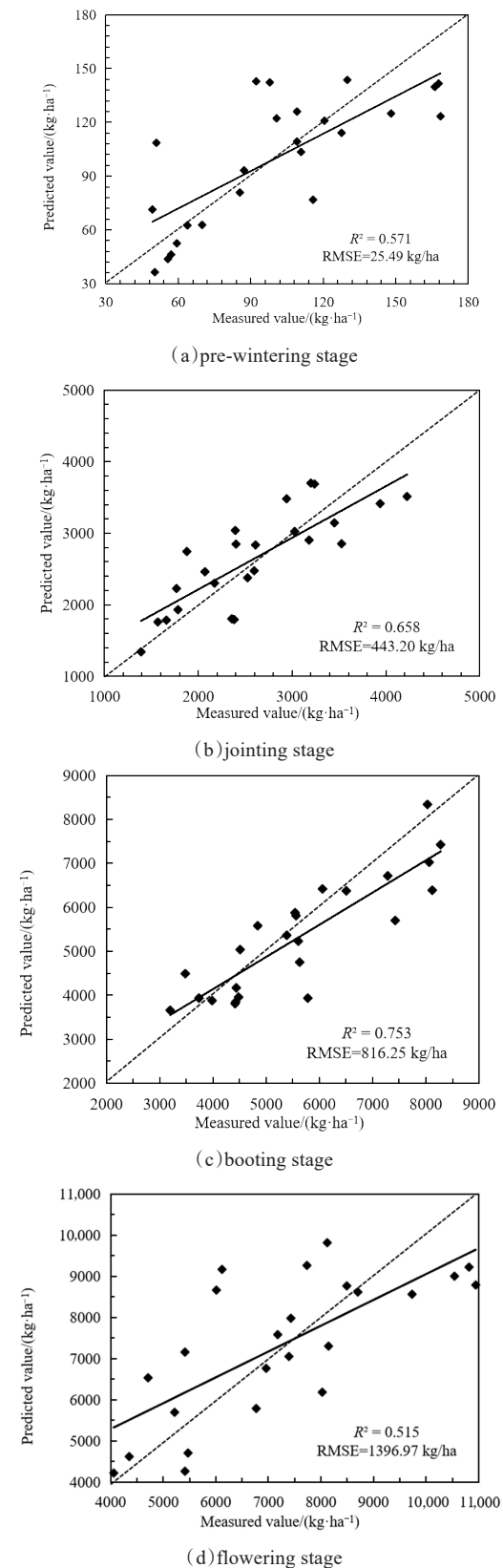


Fig. 2 Verification of wheat biomass estimation models based on color and texture feature indices

indices and four texture feature indices were calculated. The best performing color index and texture feature index were selected using correlation analysis. The results showed that the biomass estimation model constructed using a single color index could reduce the estimation accuracy due to the saturation of the image in the late growth period of wheat. In order to solve the above problems, the UAV image color and texture feature indices were combined to establish a multivariate model of wheat biomass estimation based on two types of indices, and the model was tested using independently measured biomass data, achieving an overall better performance than a single color index model.

Other studies have combined image color indices with other indices to estimate crop yield or biomass. For example, Lu et al.^[27] used UAV image data and point cloud data to estimate the aboveground biomass of wheat. Compared to the use of single color data, the model with combined indices improved the estimation accuracy, R^2 was 0.78, RMSE was 1.34 t/ha and rRMSE was 28.98%. Duan et al.^[28] established a new method combining the vegetation indices based on UAV images and the abundance information obtained from spectral mixture analysis (SMA). The results showed that the vegetation index with abundance information exhibited better predictive ability for rice yield than the vegetation index alone with the coefficient of determination reaching 0.6 and estimation error below 10%. Zhou et al.^[29] established wheat yield prediction model by using color and texture feature indices of RGB images at wheat booting and flowering stages, and the R^2 of the model increased by 2.15% and 3.69% compared with the single-color index model, respectively. The above results demonstrate that combining the color indices of UAV images with different indices, such as shape, texture, and coverage can im-

prove the estimation effect of the model.

In addition, previous studies often only monitored the biomass in a certain growth period of the crop due to image availability or other constraints, and thus the results are difficult to extrapolate. In this study, UAV images of the four key growth periods of wheat were analyzed, and the dynamic monitoring model of wheat biomass based on the UAV platform was established. The model was tested using independently measured data, and the results were all reliable, indicating that it is feasible to dynamically monitor wheat biomass using a UAV platform equipped with a digital camera, which is suitable for small and medium area applications. However, in the future, UAVs will be equipped with more types of cameras. Therefore, in future research, information such as the spectrum, color, and texture of the image could be comprehensively used to improve the monitoring accuracy and range.

5 Conclusions

In this study, estimation models of wheat biomass at main growth stages were constructed based on the color and texture index of UAV images.

Firstly, the color index and texture feature index optimally correlated with wheat biomass were identified. Among the eight color indices, most of the correlations with wheat biomass were significant, and the correlation of VARI in the pre-wintering period was the highest at $r=0.743^{**}$. The correlation of ExGR in the jointing period was the highest at $r=0.911^{**}$. The correlation of MGRVI in the booting period was high at $r=0.817^{**}$, and the correlation of VARI in the flowering period was high at $r=0.679^{**}$. The correlation between the four image texture feature indices and wheat biomass was poor, and only a few indices reached significant correlation levels.

Then, using the color indices of VARI, ExGR, MGRVI and VARI, the biomass estimation models of wheat in the pre-wintering, jointing, booting, and flowering periods were constructed, and the wheat biomass estimation multivariate models were constructed by combining the texture feature indices that with the highest correlation with wheat biomass.

Finally, the models were validated using independently measured biomass data. The results showed that both two types of estimation models passed the significance test, with the correlation reaching a significant level and the RMSE being small. The wheat biomass estimation model combined with the UAV image color and texture feature indices was better than the single color index model.

References:

- [1] WANG E. Study on remote sensing monitoring of maize growth and biomass[D]. Hefei: Anhui Agricultural University, 2018.
- [2] FAN Y, GONG Z, ZHAO W, et al. Study on vegetation biomass inversion method based on hyperspectral remote sensing[J]. Journal of Hebei Normal University (Natural Science Edition), 2016, 3: 267-271.
- [3] JIMENEZ-SIERRA D, CORREA E, BENÍTEZ-RESTREPO H, et al. Novel feature-extraction methods for the estimation of above-ground biomass in rice crops[J]. Sensors, 2021, 21(13): 1-14.
- [4] HOU X, NIU Z, HUANG N, et al. The hyperspectral remote sensing estimation models of total biomass and true LAI of wheat[J]. Remote Sensing for Land & Resources, 2012, 24(4): 30-35.
- [5] LIU Q, PENG D, TU Y, et al. Estimating forest biomass by partial least squares regression[J]. Journal of Northeast Forestry University, 2014, 7: 44-47.
- [6] YUE J, ZHOU C, GUO W, et al. Estimation of winter-wheat above-ground biomass using the wavelet analysis of unmanned aerial vehicle-based digital images and hyperspectral crop canopy images[J]. International Journal of Remote Sensing, 2021, 42(5): 1602-1622.
- [7] LI J, SHI Y, VEERANAMPALAYAM-SIVAKUMAR A N, et al. Elucidating sorghum biomass, nitrogen and chlorophyll contents with spectral and morphological traits derived from unmanned aircraft system[J]. Frontiers in Plant Science, 2018, 9: 1-12.
- [8] GU Z, JU W, LI L, et al. Using vegetation indices and texture measures to estimate vegetation fractional coverage (VFC) of planted and natural forests in Nanjing city, China[J]. Advances in Space Research, 2013, 51(7): 1186-1194.
- [9] SARKER L R, NICHOL J E. Improved forest biomass estimates using ALOS AVNIR-2 texture indices[J]. Remote Sensing of Environment, 2011, 115(4): 968-977.
- [10] CAO Q, XU D, JU H. The biomass estimation of mangrove community based on the textural features and spectral information of TM images[J]. Forest Resources Management, 2010, 6: 102-108.
- [11] MU Q, GAO Z, BAO Y, et al. Estimation of sparse vegetation biomass based on grey-level co-occurrence matrix of vegetation indices[J]. Remote Sensing Information, 2016, 1: 58-63.
- [12] LIU C, YANG G, LI Z, et al. Biomass estimation in winter wheat by UAV spectral information and texture information fusion[J]. Scientia Agricultura Sinica, 2018, 51(16): 3060-3073.
- [13] LEE K J, LEE B W. Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis[J]. European Journal of Agronomy, 2013, 48(3), 57-65.
- [14] WANG Y, WANG D, ZHANG G, et al. Estimating nitrogen status of rice using the image segmentation of G-R thresholding method[J]. Field Crops Research, 2013, 149(149): 33-39.
- [15] WANG J, ZHOU Q, SHANG J, et al. UAV- and machine learning-based retrieval of wheat SPAD values at the overwintering stage for variety screening[J]. Remote sensing, 2021, 13: 1-19.
- [16] YUE J, FENG H, LI Z, et al. Mapping winter-wheat biomass and grain yield based on a crop model and UAV remote sensing[J]. International Journal of Remote Sensing, 2021, 42(5): 1577-1601.
- [17] SHAN C, LIAO S, GONG Y, et al. Application of digital image processing for determination of vertical distribution of biomass in the canopy of winter wheat[J]. Acta Agronomica Sinica, 2007, 33(3): 419-424.
- [18] CHEN W. Evaluation of seed emergence uniformity of wheat based on UAV image[D]. Yangzhou: Yangzhou University, 2018.
- [19] GITELSON A A, STARK R, GRITS U, et al. Vegetation and soil lines in visible spectral space: A concept and technique for remote estimation of vegetation fraction[J]. International Journal of Remote Sensing, 2002, 23(13): 2537-2562.
- [20] MAO D, WU X, DEPPONG C, et al. Negligible role of antibodies and C5 in pregnancy loss associated exclusively with C3-dependent mechanisms through com-

- plement alternative pathway[J]. Immunity, 2003, 19 (6): 813-822.
- [21] WOEBBECKE D M, MEYER G E, VON BARGEN K, et al. Plant species identification, size, and enumeration using machine vision techniques on near-binary images[J]. Proceedings of SPIE-The International Society for Optical Engineering, 1993, 1836: 1-12.
- [22] HUNT JR E R, DAUGHTRY C S T, EITEL J U H, et al. Remote sensing leaf chlorophyll content using a visible band index[J]. Agronomy Journal, 2011, 103(4): 1090-1099.
- [23] TUCKER P W, HAZEN E E, COTTON F A. Staphylococcal nuclease reviewed: A prototypic study in contemporary enzymology[J]. Molecular & Cellular Biochemistry, 1979, 23(2): 67-86.
- [24] BENDIG J, YU K, AASEN H, et al. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley[J]. International Journal of Applied Earth Observation & Geoinformation, 2015, 39: 79-87.
- [25] HARALICK R M, SHANMUGAM K, DINSTEN I. Textural features for image classification[J]. IEEE Transactions on Systems Man & Cybernetics, 1973, 3 (6): 610-621.
- [26] HUNT JR E R, HIVELEY W D, FUJIKAWA S, et al. Acquisition of NIR-Green-Blue digital photographs from unmanned aircraft for crop monitoring[J]. Remote Sensing, 2010, 2(1): 290-305.
- [27] LU N, ZHOU J, HAN Z, et al. Improved estimation of aboveground biomass in wheat from RGB imagery and point cloud data acquired with low-cost unmanned aerial vehicle system[J]. Plant Methods, 2019, 15: 1-16.
- [28] DUAN B, FANG S, ZHU R, et al. Remote estimation of rice yield with unmanned aerial vehicle (UAV) data and spectral mixture analysis[J]. Frontiers in Plant Science, 2019, 10: 1-14.
- [29] ZHOU Y, WANG D, CHEN C, et al. Prediction of wheat yield based on color index and texture feature index of UAV RGB image[J]. Journal of Yangzhou University (Agricultural and Life Science Edition), 2021, 42(3): 110-116.

基于无人机图像颜色与纹理特征的小麦 不同生育时期生物量估算

戴 冕^{1,2}, 杨天乐^{1,2}, 姚照胜^{1,2}, 刘 涛^{1,2}, 孙成明^{1,2*}

(1. 扬州大学 农学院, 江苏省作物遗传生理重点实验室/江苏省作物栽培生理重点实验室, 江苏扬州 225009;

2. 扬州大学, 江苏省粮食作物现代产业技术协同创新中心, 江苏扬州 225009)

摘 要: 为实现小麦生物量田间快速无损监测, 开展基于不同密度、氮肥和品种处理的田间试验, 应用无人机获取小麦越冬前期、拔节期、孕穗期和开花期4个时期的RGB图像, 通过影像处理获取小麦颜色指数和纹理特征参数, 并同时通过田间取样获取小麦生物量; 分析不同颜色指数和纹理特征参数与小麦生物量的关系, 筛选出适合小麦生物量估算的颜色和纹理特征指数。结果表明, 不同时期图像颜色指数和小麦生物量均有较高的相关性, 且大部分达到极显著相关水平; 图像纹理特征指数与小麦生物量的相关性较差, 只有少数指标达到显著或极显著相关水平。基于上述结果, 研究利用相关性最高的颜色指数或颜色指数与纹理特征指数结合构建小麦不同生育时期的生物量估算模型, 并通过独立的实测生物量数据对模型进行了验证, 模型模拟值与实测值之间的相关性均达到了极显著水平 ($P < 0.01$), RMSE均较小。其中, 颜色指数模型在4个时期的 R^2 分别为0.538、0.631、0.708和0.464, RMSE分别为27.88、516.99、868.26和1539.81 kg/ha。而颜色和纹理指数结合的模型在4个时期的 R^2 分别为0.571、0.658、0.753和0.515, RMSE分别为25.49、443.20、816.25和1396.97 kg/ha, 说明模型估算的结果是可靠的, 且精度较高。同时结合无人机图像颜色和纹理特征指数的小麦生物量估测模型的效果要优于单一颜色指数模型。研究可为小麦田间长势实时监测与生物量估算提供新的手段。

关键词: 小麦; 无人机图像; 颜色指数; 纹理特征指数; 生物量; 纹理指数

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